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A Comprehensive Analysis of LDA, SVM, and Neural Network Algorithms in Multiclass Myoelectric Identification of Limb Movements

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Abstract - This study investigates the processing of Electromyography (EMG) signals, incorporating a lowpass filter at 400 Hz, a highpass filter at 20 Hz guided by Fast Fourier Transform (FFT) analysis, and Root Mean Square (RMS) analysis with 150 ms windows for feature extraction. The research evaluates Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Neural Network (NN) algorithms for classifying 11 different hand positions. High precision, recall and F1 scores are observed in these algorithms, where the Multilayer Perceptron Neural Network (MLP) exhibits superior performance (F1 score: 99.9%). These findings highlight the efficiency of optimized EMG signal processing in achieving accurate hand position classification in prosthetic hands.

Keywords – EMG, Linear Discriminant Analysis, Neural Networks, Support Vector Machine, Signal Processing, Prosthetics

1. Introduction

Hand position classification from muscular activity is crucial in prosthetic hands. The exploration of electromyography (EMG) signal process has a significant role in understanding and interpreting neuromuscular activities. This paper investigates EMG signal processing and classification, focusing on reaching successful results in classification by applying beneficial preprocessing and feature extraction methods.

This study includes three prominent signal classification algorithms—Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Multilayer Perceptron Neural Network (MLP)—into the assessment framework. Our research problem focuses on the accurate detection and classification of 11 distinct hand positions which are widely used positions in prosthetic hands. The following evaluation, grounded in established metrics including recall, precision, and F1 scores, seeks to determine the effectiveness of every algorithm in the framework of our signal processing methodology.

In addition to the comparative analysis of hand position classification algorithms, the usefulness of machine learning in myoelectric identification is examined in this study. Acknowledging the pivotal role of machine learning methodologies in accurately recognizing and interpreting myoelectric signals, we extend our exploration beyond mere comparison. Our research intends to advance knowledge of myoelectric signal processing and its applications in prosthetics by emphasizing how machine learning models can enhance prosthetic functionalities in this field.

The complexity of controlling finger gestures, in contrast to wrist or hand movements, has been a prominent focus in the literature on electromyography (EMG) signal processing. The distinctive challenge arises from the comparatively smaller amplitudes of EMG signals generated during finger movements, presenting difficulties in the accurate interpretation of the signal. Researchers have acknowledged and addressed this challenge, emphasizing the need for advanced signal processing techniques to navigate the complexities of finger-specific EMG signals effectively. Moreover, investigations into the forearm's deep layers have revealed that these layers house the muscles responsible for directing finger movements. This anatomical consideration adds another layer of complexity to the control of finger gestures [1].

In the following sections, we present our methodology, experimental results, and discussions, highlighting the effective integration of LDA, SVM, and MLP as machine learning algorithms in myoelectric identification and the transformative possibilities they bring for hand prosthesis applications. This work advances the field of controlling prosthetic systems and emphasizes the critical role of neural network algorithms play in these developments.

2. Related Work

In commercial prosthetic hands, different numbers of EMG sensors are used. It can be observed that a limited number of EMG sensors constrain users to a predefined set of hand gestures. Enhancing the functionality of myoelectric prostheses has become a key focus in related literature. Researchers are actively investigating ways to advance EMG signal processing to incorporate more control patterns, aiming to provide users with a wider range of gestures and increased versatility in prosthetic limb control [2].

In the acquisition of electromyography (EMG) signals, two predominant methods, surface and intramuscular, are commonly employed. Signals obtained from surface nodes typically exhibit small amplitudes, usually in millivolts, and are susceptible to line and skin impedance noise. As a prerequisite for further processing, signal conditioning is essential for these EMGs. The challenges associated with signal quality and noise mitigation during acquisition underscore the importance of effective signal conditioning methodologies, a crucial aspect addressed in the literature on EMG signal processing [3].

Surface electromyography (sEMG) offers noninvasive, real-time, and user-friendly advantages with the capacity for multi-point measurements.[2]. EMG-based systems are especially advantageous for amputees and individuals with weak muscles, requiring only muscle activation rather than physical movement. This adaptability makes them well-suited for diverse user profiles in the context of prosthetic control systems [1].

Following signal acquisition, feature extraction emerges as a crucial step, facilitating the identification and extraction of valuable information embedded in the signals. These feature vectors play a significant role in training, validation, and testing processes within the classifier for subsequent signal classification [3].

In order to make feature extraction better, continuous signals are subdivided into appropriate sizes using window functions. Features are then extracted from each window, and the attributes of these features significantly impact the performance of gesture recognition systems. Factors such as the number and type of features play a key role in real-time accuracy. In signal analysis, time-domain and frequency-domain features are prominent. In this context, the extraction of root mean square (RMS), waveform length (WL), and median amplitude spectrum (MAS) as key time-domain features. Leveraging these features demonstrates promising classification results, leading to their utilization as input parameters for the identification network [4]. Root Mean Square (RMS), a widely utilized statistical feature in vibration signal analysis, is modeled as an amplitude-modulated Gaussian random process. This versatile representation is particularly relevant in contexts involving constant force and non-fatiguing contractions, displaying its efficiency in signal processing applications. [5]

Following feature extraction, a classifier is essential for obtaining the gesture label of the signal. Various classifiers, including linear discriminant analysis (LDA), support vector machines (SVM), and artificial neural networks (ANN) such as the multilayer perceptron classifier (MLP), have been used in related studies. These diverse classifier options reflect the ongoing exploration of effective models for accurately categorizing electromyography signals in gesture recognition systems [6].

Linear discriminant analysis (LDA) offers a notable advantage in its simplicity of implementation, particularly on embedded processors, and its ease of training. This characteristic makes LDA an appealing choice for applications where computational efficiency and straightforward training processes are paramount considerations [7].

Support vector machines (SVM) utilize the powerful concept of a kernel function, enabling these models to manage separations with highly complex boundaries. The kernel function's role is to map the data into a different space, where a hyperplane becomes effective in achieving the desired separation. This inherent flexibility in handling complex relationships contributes to the efficiency of SVM models in various classification tasks [8]

Artificial neural networks (ANN), known for their capacity to capture system nonlinearity and maintain a low computational load, exhibit promising performance in classifying motion-based signal patterns [1]. Specifically, a Multi-layer Perceptron (MLP) network, a specialized type of ANN, has been widely employed for signal classification [5]. Notably, in the context of Myoelectric Signals, most of the research utilizes MLP networks, emphasizing their effectiveness and ease of application in handling myoelectric signals [9].

3. Methodology

In this study, we improved and processed electromyographic (EMG) data, identified muscle patterns by identifying important aspects, and classified the results using machine learning. In the last stage, performance metrics and model accuracy were carefully evaluated. Our method shows how machine learning can effectively identify EMG data and provide a deep understanding of muscle movements. Flowchart of the methodology shown in Figure 1 below.

Figure 1: Flowchart of the study

In Figure 2, the hand positions which are classified are illustrated. Data is collected while keeping the hand in static positions for 10 seconds. Signal levels for each channel are observed during collection, same levels are tried to protect during positions. 8 EMG sensors were placed on forearm in such a way as to wrap the arm circularly, and positions are not specified since it is a usual application in commercial products.

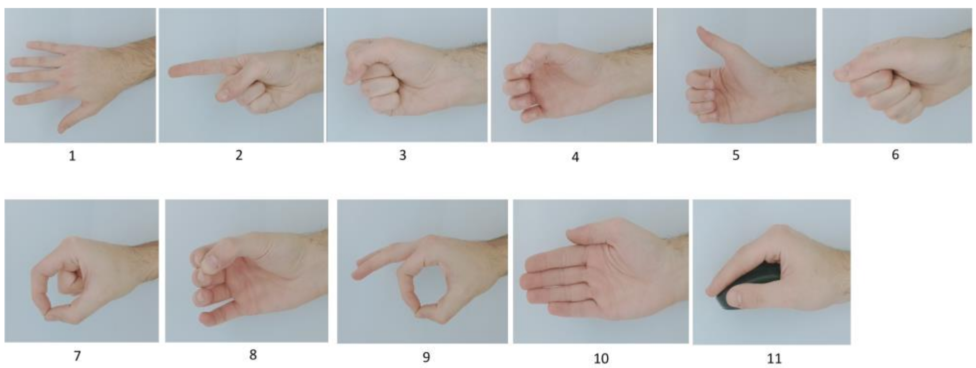

Figure 2: 1) Rest Position 2) Active Index Grip 3) Power Grip 4) Pinch Grip 5) Hook Grip 6) Key Grip 7) Precision Closed Grip 8) Tripod Grip 9) Precision Open Grip 10) Open Palm Grip 11) Mouse Grip

4. 3.1 Surface EMG (sEMG) Data Acquisition

In this study, sEMG data was acquired using an STM32F407G microcontroller monitored and saved. The microcontroller facilitated high-speed analog-to-digital conversion. Raw sEMG signals were conditioned for accuracy before being transmitted in real-time via serial communication, at a baud rate of 921600 baud/s. Data is collected through sEMG sensor which has an analog bandpass filter that filters signals between 50 Hz and 500 Hz. Data was monitored with a sampling rate of 1000 Hz. In figure 3, the setup can be seen.

Figure 3: Data Acquisition System

In the context of the comprehensive experimental setup, the participant maintained a fixed posture for each designated hand position. Eight electromyography (EMG) measurements, spanning a duration of 10 seconds, were systematically recorded for each distinct hand position.

5. 3.2 Data Preprocessing

6. 3.2.1 Fourier Transform Analysis

The decision to use the Fast Fourier Transform (FFT) as an analysis tool is rooted in its capability to provide a comprehensive frequency domain representation of the signal. By applying FFT to the raw EMG signal, we gain insight into the distribution of frequency components. This analysis aids in establishing appropriate cutoff frequencies for the lowpass and highpass filters. The result of FFT analysis is shown in Figure 3 below.

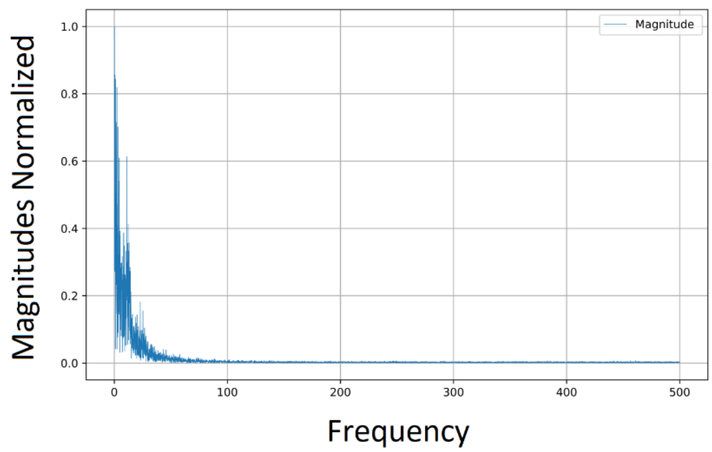

Figure 4: Frequency analysis on EMG data

7. **3.2.2 Identification of Dominant Frequencies:**

The FFT analysis allows us to identify the dominant frequencies present in the raw EMG signal. The majority of muscle activity typically falls within the lower frequency range, justifying the choice of a lowpass filter at 400 Hz to minimize the impact of electrode and equipment noise. [10],

8. **3.2.3 Mitigation of Noise:**

Low-frequency noise and interference, often originating from external sources, can be effectively identified through FFT analysis. This information guides the application of a highpass filter at 20 Hz to eliminate unwanted low-frequency components.

9. **3.2.4 Frequency Filtering:**

Filters were applied cumulatively to the raw data. A comparison of filtered and raw data is shown in the graphs in Figure 4. It can be seen that the noise is eliminated as desired.

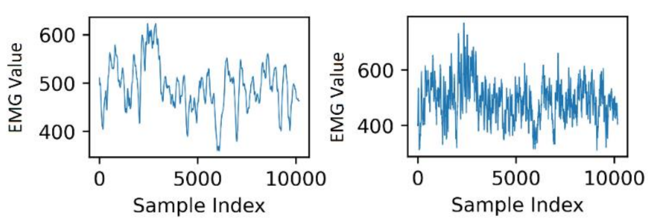

Figure 4 Filtered and Raw EMG Data, for a Specified Channel and Hand Position

3.3 Feature Extraction

10. **3.3.1 Root Mean Square Analysis**

Root Mean Square (RMS) analysis (Eqn. 1) is a valuable technique for quantifying the amplitude of a signal by considering the square of the signal values over a specified window. Commonly embraced for its effectiveness, RMS stands out as a widely favored option for minimizing noise, especially in static electromyography (EMG) conditions. The choice of window size is a critical parameter in RMS analysis, influencing the temporal resolution and the ability to capture relevant information.

The chosen window size of 150 samples corresponds to a specific time duration of 150 milliseconds within the signal, with the assumption of a consistent sampling rate. This window size achieves a balance between obtaining a sufficiently detailed representation of the signal, maintaining a reasonable temporal resolution. Additionally, classification performance for RMS is almost stable after sample information of 150 ms.

11. 3.3.2 RMS Results

Features of each channel of every position are extracted using RMS statistical analysis. Feature extracted result of one of the channels in a position with 5000 samples is shown in Figure 5 below.

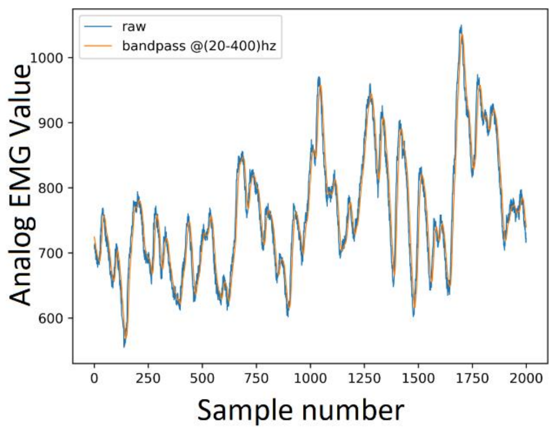

Figure 5 RMS Applied Data and Preprocessed Data

12. 3.4 Classification

After feature extraction, the classification process involves the utilization and comparison of three distinct algorithms: Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Multi-layer Perceptron (MLP). In this study, 70% of the dataset was used for training and 30% for testing. These methods are commonly used in similar research for the classification of EMG signals [7-9]. These algorithms were chosen to not only assess their success in accurately classifying myoelectric signals but also to investigate their applicability in prosthetic hand control algorithms.

13. 3.4.1 Linear Discriminant Analysis (LDA)

LDA, employed for multiclass classification, utilizes the Singular Value Decomposition (SVD) solver, implemented through the Scikit-learn package in Python The choice of LDA is motivated by its simplicity of implementation and suitability for embedded processors, aligning with its potential application in prosthetic hand control.

14. 3.4.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) was applied for multi-class classification with a one-versus-the-rest multiclass approach with a radial basis kernel. The SVM implementation utilizes the scikit-learn package in Python, allowing for the effective handling of myoelectric signal separations with complex boundaries. The assessment focuses on evaluating the capability of SVM in accurately classifying myoelectric signals, exploring its suitability for prosthetic hand control.

15. 3.4.3 Multi-Layer Perceptron (MLP) Neural Network

Multi-layer Perceptron (MLP), a specialized type of Artificial Neural Network (ANN), a single hidden layer with 15 neurons is implemented. The rectified linear activation functions are used, and the MLP is executed using the scikit-learn package in Python. To maintain the optimal computational load for prosthetic hand applications, the Multi-layer Perceptron (MLP) is designed with a single layer and 15 neurons with rectified linear activation functions. This choice optimizes accuracy while ensuring efficient real-time processing on microcontrollers commonly used in prosthetic hands The evaluation aims to understand the performance of this configuration in myoelectric signal classification and its potential application in prosthetic hand control algorithms.

16. Results and Discussion

The evaluation and comparison of the three classification algorithms Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Multi-layer Perceptron (MLP)were conducted based on key performance metrics, specifically recall, precision, and F1 score. These metrics offer a comprehensive understanding of the algorithms' effectiveness in myoelectric signal classification for prosthetic hand control.

17. 4.1 Linear Discriminant Analysis (LDA):

LDA, implemented for multiclass classification with the scikit-learn package in Python, exhibited exceptional performance with an F1 score of 99.34%, a precision score of 99.37%, and a recall score of 99.33%. The model is trained by maximizing the ratio of between-class variance to within-class variance, and errors are calculated based on the difference between predicted and actual class labels. The confusion matrix (Figure 6) provides a detailed view of classification results, showcasing LDA's effectiveness in distinguishing between different hand gestures.

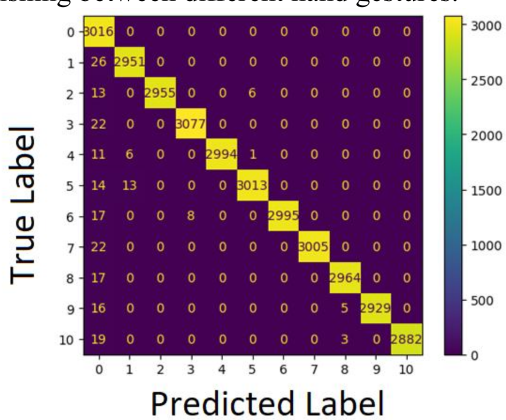

Figure 6: Confusion Matrix of LDA

18. 4.2 Support Vector Machine (SVM):

Utilizing the scikit-learn package in Python with a one-versus-the-rest multiclass approach and a radial basis kernel, SVM showcased robust performance with an F1 score of 99.80%, a precision score of 99.80%, and a recall score of 99.80%. The training involves finding the hyperplane that maximally separates classes, and errors are determined by the margin between data points and the decision boundary. The confusion matrix (Figure 7) illustrates the classification outcomes, emphasizing SVM's ability to handle complex signal separations and its applicability for prosthetic hand control.

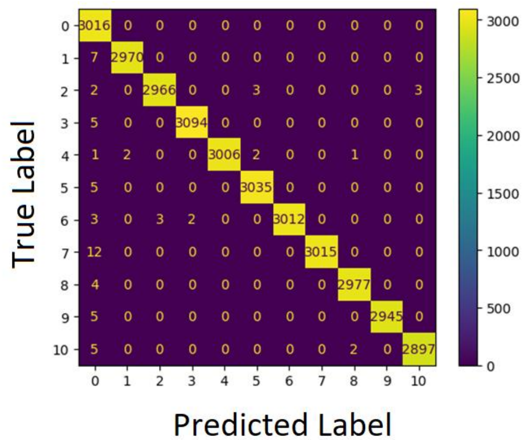

Figure 7: Confusion Matrix of SVM

19. 4.3 Multi-layer Perceptron (MLP):

The MLP, featuring one hidden layer with 15 neurons and rectified linear activation functions from the scikit-learn package in Python, demonstrated an outstanding F1 score of 99.99%, a precision score of 99.99%, and a recall score of 99.99%. The MLP classifier is trained by iteratively adjusting weights and biases to minimize prediction errors, calculated as the difference between predicted and actual outputs. Stochastic gradient based optimizer was employed for this purpose, using a loss function to quantify errors. The confusion matrix (Figure 8) provides a visual representation of classification results, highlighting MLP's efficacy in capturing nonlinearity in myoelectric signals.

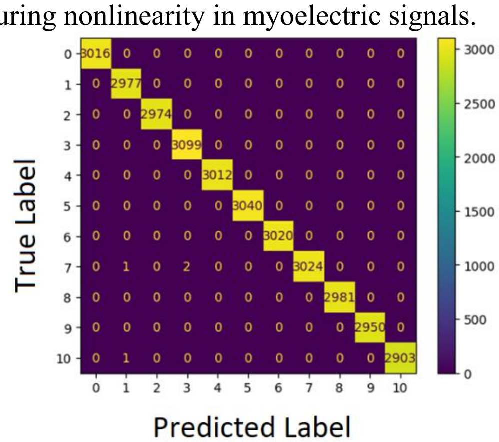

Figure 8: Confusion Matrix of MLP

The evaluation metrics—precision, recall, and F1 score—showed subtle differences in the algorithms' performances. LDA produced noteworthy metrics and achieved success in simplicity., while SVM showcased robustness in handling complex signal separations. MLP, with its distinctive architecture, demonstrated competitive performance, emphasizing its potential for capturing nonlinearity in myoelectric signals.

Confusion matrices are included to improve our comprehension of algorithmic performance by defining distinct categorization results for every hand gesture. The strengths and areas of performance of LDA, SVM, and MLP provide a basis for thoughtful decision-making in the development of prosthetic hand control algorithms.

20. Conclusion

In conclusion, this study underscores the practical success of Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Multi-layer Perceptron (MLP) algorithms in prosthetic hand control, particularly with large myoelectric datasets. MLP resulted with highest F1 score of 99.99%, while LDA has an F1 score of 99.34%, and SVM has an F1 score of 99.80%. These algorithms showcase their applicability in real-world scenarios. LDA's simplicity, SVM's robustness, and MLP's nonlinearity capturing ability highlight their collective effectiveness.

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